Robust Color Choice for Small-size League RoboCup Competition

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ABSTRACT

In this paper, the problem of choosing a set of most separable colors in a given environment is discussed. The proposed method models the process of generating theoretically computed best colors, printing of these colors through a color printer, and imaging the printed colors through a camera into an integrated framework. Thus, it provides a feasible way to generate practically best separable colors for a given environment with a set of given equipment. A real world application (robust color choice for small-size league RoboCup competition) is used as an example to illustrate the proposed method. Experimental results on this example show the competitiveness of the colors learned from our algorithm compared to the colors adopted by other teams which are chosen via an extensive trial and error process using standard color papers.

Keywords: Robocup, Color Space, Color Perception, Color Imaging, Color Image Communication.

1. INTRODUCTION

For many vision applications, such as robot navigation, colors are adopted to aid the identification of target objects. This raises the problem of how to choose a set of suitable colors for a given environment. Since there are existing colors in most environments, the newly chosen colors need to be as separable as possible from those existing colors and also need to be distinguishable from each other. It is generally a difficult problem, because there is a significant difference between theoretically designed colors and the actual colors produced by any equipment, such as printer, camera, framegrabber etc. For instance, the gamma correction facility of a CCD camera can cause not only an increase in electronic noise but the non-linear response to light intensity as well [1]. Usually, the produced colors are only approximations of the theoretical colors according to their device dependent physical models, e.g, the same color printed on a color printer looks significantly different from the one rendered on a CRT. The reason lies in the fact that cross-media image reproduction is a complicated process concerned with three essential elements: device characterization, color appearance modeling and gamut mapping [2]. This is one of the fundamental problems in color image communication, which affects researchers who wish to accurately display color in archival journals for many years. Unfortunately, sending a color print to the publisher does not guarantee a close match [3]. One approach to quantify the transformations that occur on the image, is to include color samples of known CIE values with each image. The change on these colors would provide an indication of the types of change that occurred on the published image [4]. This method can be regarded as one kind of color gamut mapping, which assigns colors from the reproduction medium to colors from the original medium [2]. However, accurate hard-copy color image production is a difficult problem due to the large variety of devices that are used and due to the inherent nonlinearity of the process [5]. Therefore, there is no simple universal mode that can be used in describing the transformation from one color device to the other even though they representing the same color content. On the other hand, illumination conditions also have great effects on the recorded color images, which means the color correction is generally required after scenes are captured by any camera type device. For example, a color imaging system is likely to skew colors according to the illumination and it can only balance colors under one specific illumination condition without color correction [2]. Therefore, the problem of designing separable colors is not only device dependent but also environment dependent.

In this paper, we focus on a practical solution of choosing separable colors in a given environment with common equipment without relying on any complicated device color models. By “practical”, we mean the designed colors need to be printed out and re-imaged through cameras to get the final perceived colors, where these perceived colors need to be widely separable, so that the vision system can take advantage of these widely separated perceived colors for object detection and tracking. This is difficult because the entire design process is divided into three separate stages, color designing, color printing and color imaging. The printing and imaging process distorts the designed colors, which results in differences between the theoretically designed colors and the actual perceived colors.

The requirement of designing a set of widely separable colors as team and orientation marks for identification of robots in the small size league RoboCup competition inspired this work. RoboCup Soccer is an attempt to promote artificial intelligence (AI) and robotics research by providing a common task for evaluation of various theories, algorithms, and agent architectures. In order for the robot (physical robot and software agent) to play a soccer game reasonably well, a wide range of technologies need to be integrated and a number of technical breakthroughs must be accomplished. The range of technologies spans both AI and robotics research and includes design principles of autonomous agents, multi-agent collaboration, strategy acquisition, real-time processing and planning, intelligent robotics, sensor fusion, and so forth [6] [7] [8] [9].

A small-size robot soccer game takes place between two teams of five robots each. The robots play soccer on a green-carpeted field that is 2.8m long by 2.3m wide with an orange golf ball (new rule has extended the field to 5.5m long and 4m wide). Robots come in two varieties, those with local on-board vision sensors and those with global vision. Global vision robots, by far the most common variety, use an overhead camera and an off-field PC to identify and track robots as they move around the field. The overhead camera is attached to a camera bar located 4m above the playing surface. The standard RoboCup vision system consists of everything from the lighting and markers on top of the robots, to the acquisition and processing of visual data, through the transmission of the processed data to the artificially intelligent programs. The vision system processes a colored image from a CCD camera to locate and track ten robots and a ball. Processing segments the image, locates interesting objects, and identifies and tracks these objects. Special colors are used as marks which include: orange (the color of the ball), yellow to signify the mark for one team, blue to signify the mark for the other team, white to signify the walls, field lines, and the orientation of the robots, green to signify the playing field, and black to signify the robot bodies (excluding markings). Each individual team may design its vision system to take its own orientation color into account as long as it is not one of the special colors mentioned above. Robust color choice is a very important issue in achieving highly accurate detection under different illumination conditions. In theory, color-based detection is a relatively simple vision problem, but it turns out to be more difficult in the real world. It is very important to choose the right color to assure that color patterns will not be confused anywhere on the field, because shadows and non-uniform illumination are prevalent on the field.

In this paper, we present a general strategy which integrates the modeling process of color design, color printing and color imaging. It can be used to choose practically best separable colors in a given environment with given equipment. The printing and imaging processes are treated as black-boxes, and their effects of distorting colors are stated as a system identification problem. Parametric forms are adopted to model this distortion for its simplicity. We use the RoboCup color pattern design problem as an example to illustrate the detail of our proposed general strategy.

Fig. 1. An example environment

The paper is divided into seven sections. In section 2, the problem of robust color choice for RoboCup is stated. Section 3 presents the general strategy of solving the problem. Section 4 is devoted to discussing the theoretical and practical achievable color space. Parametric models are presented in section 5. In section 6, simple geometric approaches are used to find the practically best separate colors. Finally, conclusions are drawn in section 7.

2. PROBLEM STATEMENT

In this paper, we consider the problem of designing widely separable colors in a given environment that need to be as separable as possible from colors existing in the environment and are distinguishable from each other. These colors are widely separable in the scene being re-imaged through a camera into perceived colors, so that the color based segmentation and object detection will be simplified for the associated vision system. These designed colors will be used as the candidate colors of team marks and orientation marks, which are put on the top of the robots for identification in the small size league RoboCup competition. An example of such environment is displayed in Figure 1. The equipment necessary for this application is a color inkjet printer, a camera and its associated capturing devices. In our experiments, we use an Epson Stylus C82 as the color printer and Sony XC 999 as the camera.

3. GENERAL STRATEGY

Since there is a significant difference between the theoretically designed colors and the actual produced colors, modeling processes need to study this distortion. It is also important to consider the luminance and color separately, which greatly simplifies algorithm design and saves the cost of printing calibration samples. Our proposed general strategy can be divided into seven major steps:

1. Transform the RGB space to YCbCr space so that the color and luminance can be treated separately.
2. Study the theoretical color and luminance range and prepare color and luminance calibration samples.
3. Build parametric models for the sampled practical colors which are generated by the imaging of the color calibration samples.
4. Establish the mapping from theoretical colors to their corresponding practical colors.
5. Approximate the existing colors in the given environment with a simple parametric model.
6. Place the required number of points (colors) on the maximum achievable practical colors (some parametric curves) so that the minimum distance from these points to the existing colors is maximized and the distance between these points is as large as possible.
7. Map the resulting practical colors to theoretical colors, convert them back to RGB color space and print them out as candidates for RoboCup patterns.

4. COLOR SPACE

For the reasons discussed in the previous section, luminance and color are treated independently. In this work, the YCbCr color space is adopted to decompose the 3D color vector to one 1D luminance term and one 2D color component. The conversion formula from RGB to YCbCr is [10]:

$$\left\{ \begin{array}{c} Y = 0.257 \times R + 0.504 \times G + 0.098 \times B + 16 \\ Cb = -0.148 \times R - 0.291 \times G + 0.439 \times B + 128 \\ Cr = 0.439 \times R - 0.368 \times G - 0.071 \times B + 128 \end{array} \right. \tag{1}$$

The range of RGB space is $[0, 255]$, therefore with Eq. (1) the theoretical range of Y is $[16, 235]$, and the range of (Cb, Cr) is shown as the white region in Figure 2. The actual produced color range after printing and re-imaging through the camera has significant difference from theoretical color range. In order to estimate the practical range of the luminance (Y) and color (Cb, Cr), we print out a set of luminance and color calibration samples and re-image them with the camera.

For the study of practical luminance range, the Cb and Cr value is fixed to 128, and the Y value ranges from 16 to 235. Figure 3 shows the relationship between the theoretical luminance values and practical luminance

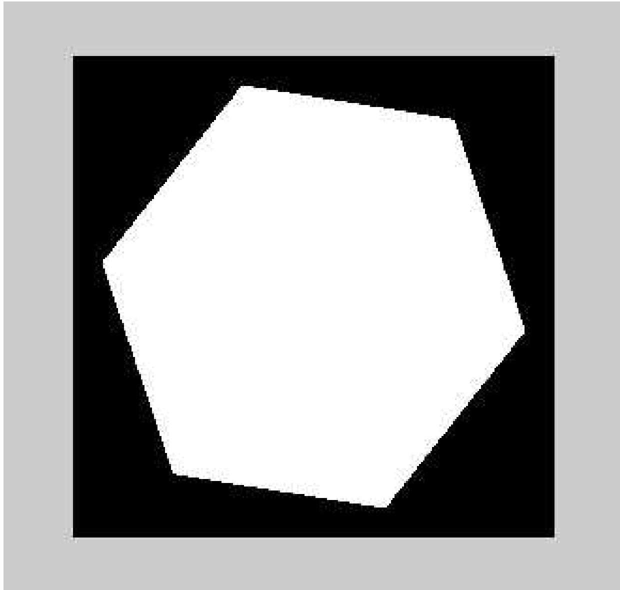


Fig. 2. Theoretical color range

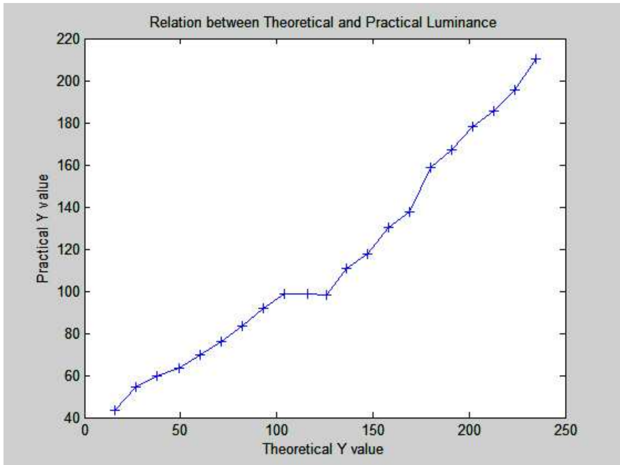


Fig. 3. Relation with theoretical and practical luminance values

values. 21 patterns with different Y values are printed out as luminance calibration samples. From Figure 3, it is evident that the practical luminance range is slightly smaller than the theoretical range in this given environment.

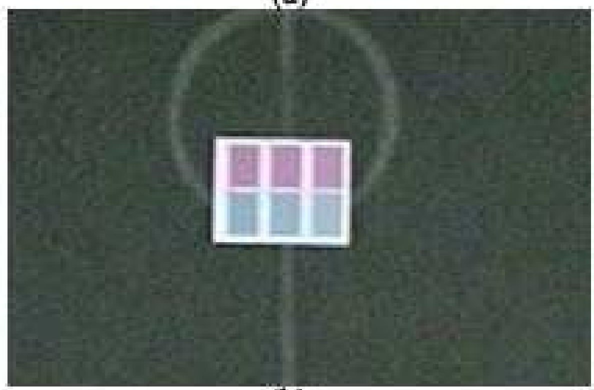
To determine the practical range of achievable colors (Cb, Cr), we prepare color calibration samples. As stated in section 2, the aim of color design is to select colors that are maximally separable to existing colors and also keep them as separable as possible from each other. Therefore, it is natural to choose the colors from the boundary of the maximum achievable color space. The theoretical boundary is a hexagon on which the parametric representation of the point has to be divided into six different sections. We consider the maximum inner circle of the theoretical Cb, Cr range as shown in Figure 2, which is centered at

$(128, 128)$ with the radius equal to 98. A circle is adopted for sampling positions in the color space because it has a simple point representation and also encodes simple mapping relationships from theoretical colors to practical color, which will be demonstrated in section 5.2. By equally sampling the circle, we can get the theoretical Cb and Cr values. In order to generate color calibration samples, we have to determine the Y values for each of the (Cb, Cr) set. One natural choice seems to be always choosing the maximum allowed Y value, but this is not feasible. Fixing Cb and Cr values in Eq. (1) creates an upper-bound on how large Y can be. Y can be represented using R, Cb and Cr as:

$$\begin{aligned} Y &= 0.859 \times R + 0.0015 \times (Cb - 128) - \\ &\quad 1.37 \times (Cr - 128) + 16 \end{aligned} \tag{2}$$

From Eq. (2), it is evident that there exists a set of Y values that is competitive to a fixed set of (Cb, Cr) values, and by changing the value of R we can adjust the luminance value. If we do a luminance histogram analysis of the environment shown in Figure 1, its luminance is concentrated in the dark portion. Thus, it is suitable for us to choose as large a Y value as possible for generating color calibration samples and final colors as well. In total, 36 colors are equally sampled from the circle. With the proper choice of luminance value as discussed above, we can determine the theoretical color values of calibration color samples. After printing, these calibration samples are re-imaged with the camera to generate practical colors. Figure 4 shows the color samples and the actually perceived colors after the samples being printed out and re-imaged through camera. It is obvious that color distortion happened during the printing and re-imaging process. Figure 5 shows the relationship between the theoretical colors and practical colors. The blue points denote the theoretical colors on the circle, and the red points are the practical colors. The yellow lines between the theoretical colors and the practical colors denote the one to one correspondence between them. It is evident from Figure 5 that there are significant differences between the theoretically designed colors and practically produced colors. By treating luminance and color separately, we reduce the number of calibration samples required from 756 to 57.

(a)



(b)

Fig. 4. Color samples and re-imaged colors

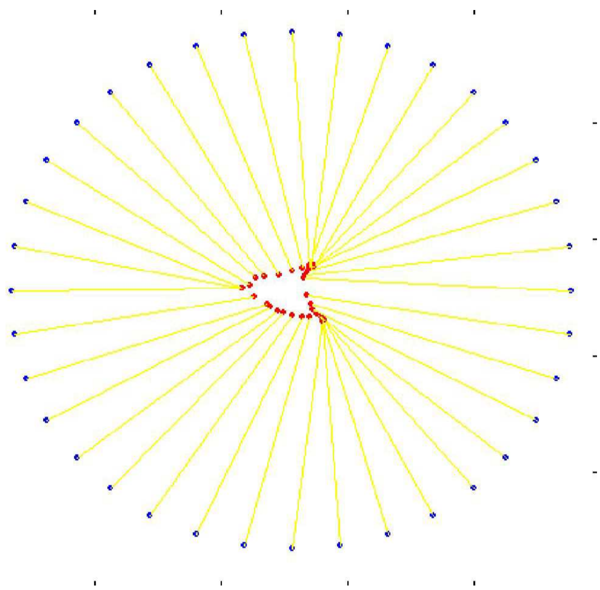


Fig. 5. Relation between theoretical and practical colors

5. PARAMETRIC MODELS

There are three parametric models involved in our design. First, a piecewise continuous parametric model is proposed to describe the produced practical colors from the color calibration samples. Second, the mapping relationship between the theoretical colors and practical colors needs to be estimated. Third, a parametric model is required to approximate the existing colors in the environment.

Parametric Model for Practical Colors

For this specific example, we can observe in Figure 4 and 5 that practical colors can be divided into three pieces so that each piece can be fitted by simple parametric models with reasonable accuracy. Here, we use a circle fit as the parametric model to fit the practical colors because it is easy to set up a mapping between the theoretical circle as show in Figure 5 to the partial fitting circle of the practical colors. It can be computed that the resulting three circle functions are

$$\begin{cases} (x-146.31)^2+(y-129.32)^2=13.66^2 \\ x<146.31, 117\leqslant y\leqslant 137 \end{cases} \tag{3}$$

$$\begin{cases} (x-132.11)^2+(y-102.8)^2=34.71^2 \\ 108\leqslant x\leqslant 136, y>125 \end{cases} \tag{4}$$

$$\begin{cases} (x-138.71)^2+(y-157.22)^2=41.06^2 \\ 108\leqslant x\leqslant 142, y<128 \end{cases} \tag{5}$$

Figure 6 shows the three partial circles that piecewisely fit the produced practical colors. The black points in Figure 6 denote existing colors in the environment and the red points are the re-imaged calibration colors that are piecewisely approximated by three partial circles. The blue colored partial circle corresponds to Eq. (3). The black colored partial circle corresponds to Eq. (4). The green colored partial circle corresponds to Eq. (5). Since the sample colors are designed to approximate the boundary of the theoretically achievable colors, it is assumed to be approximately the largest achievable practical color space for a given setting e.g. illumination, camera, printer etc. Although, this assumption is not absolutely accurate (see Fig. 6, a little portion of the existing colors represented by the black points pass the boundary of the green circle), it is the simplest assumption which leads to a search algorithm described in section 6. The experimental results also show that the assumption is reasonable for generating practically separable colors.

Mapping from Theoretical Colors to Practical Colors

A simple geometric methodology is adopted to set up the correspondence between a color on the theoretical circle and a color on one of the partial circles. 2D affine transform is one of the most widely used technologies in general point mapping [11]. However, the affine transform cannot encode the fact that these 2D points are located on some specific trajectories. Thus special considerations should be made taken to address the fact that these points are all located on some circles. Since the practical colors are approximated by three partial circles, there will be three separate mappings (one for each partial circle). In Figure 6, the blue partial circle on the right corresponds to the partial theoretical circle with angles ranging from $\left(-\frac{\pi}{3},\frac{\pi}{3}\right)$, the black partial circle on the top corresponds to the partial theoretical circle with angles ranging from $\left(\frac{\pi}{3},\pi\right)$, and the green partial circle corresponds to the partial theoretical circle with angles ranging from $\left(\pi,\frac{5\pi}{3}\right)$. Figure 7 illustrates the general principles of mappings between two different circles with different radius and

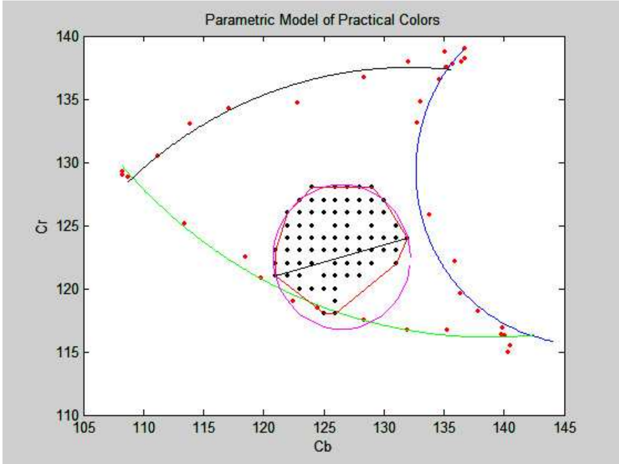


Fig. 6. Parametric model of practical colors

centers, where $d\left(x,y\right), c\left(x_c,y_c\right)$ and o represent the position of theoretical colors and the center of the theoretical circle. Similarly, $d^{'}\left(x,y\right), c^{'}\left(x_c,y_c\right)$ and $o^{'}$ are the corresponding elements on the practical partial circle. By assuming the practical colors are equally placed on the partial circle, it can be deduced that if the arc triangle $\left(d\left(x,y\right), o, c\left(x_c,y_c\right)\right)$ occupies p percentage of the total area of the theoretical partial circle, then its corresponding arc triangle $\left(d^{'}\left(x,y\right), o^{'}, c^{'}\left(x_c,y_c\right)\right)$ occupies the same percentage on the small partial circle. With both end points known as a prior the mapping relationship is uniquely determined. This simple geometric assumption yields fast solutions for generating the corresponding colors between theoretical and practical color boundaries. Although, Figure 7 only demonstrates the case of the mapping between a convex partial circle to a convex partial circle, the same principle holds for the mapping between a concave partial circle to a convex partial circle, which is the case of the blue partial in Figure 6.

Approximation of Existing Colors

Colors in the environment are also transformed to YCbCr color space and occupy some regions on the (Cb, Cr) plane as shown in Figure 6 (represented as black points). A circle is used to approximate the convex hull of the existing colors. As shown in Figure 6, the red polygon is the convex hull of the existing colors, and the magenta circle is the approximation coverage circle of the existing colors. We choose a circle as the approximation of existing colors for easy computation of the T set which will be discussed in the next section.

6. FINDING THE BEST COLORS

With the development of the parametric models, the problem stated in section 2 is simplified to finding a set of points on three partial circles so that the minimum distance from these points to the existing colors is maximized. At

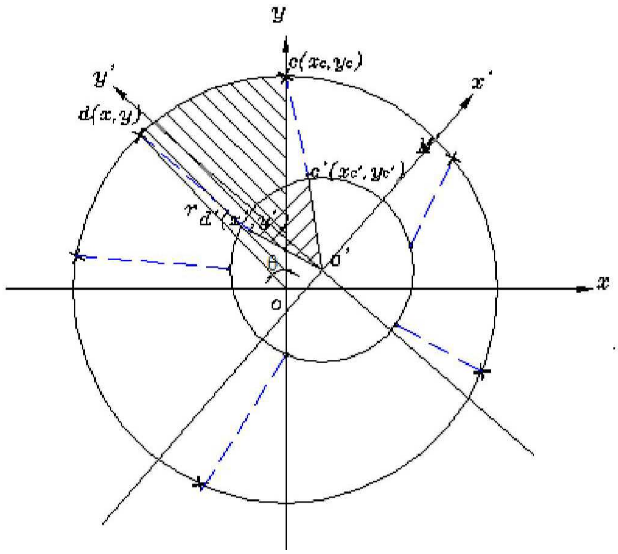


Fig. 7. Mapping between theoretical and practical colors

the same time the distances among these points are as large as possible. These points are mapped back to the theoretical circle as desired colors together with the proper choice of luminance to generate candidate colors for the RoboCup application. Since the approximated circle of existing colors has an intersection with the practical partial circle and the practical colors are approximated by three pieces of partial circles, it is generally a difficult task to determine the placement of points on these partial circles. Instead of seeking accurate solutions to this problem (that may not exist in the general case), we propose to use a simple geometric method to estimate the placement.

A T set is defined to represent the points on the partial circles from which the distance to the existing color circle is at least T. If we place a set of approximately equal distant points on the T set, these points are at least T far away from the existing color circle. Let S denote the minimum distance among these points. As long as the number of points needed to be placed is not too large, S is always larger than T for some initial small T values. If we gradually increase T, S gradually decreases. We choose the time when S equals T as the approximated solution for our problem. Figure 8 shows two T sets corresponding to 2 and 7, respectively.

As shown in Figure 8, the T set is composed of different partial circles. Furthermore, it breaks the original three pieces of the partial circle into two disconnected parts. It is very difficult to accurately distribute points equally on the T set. Instead of looking for the accurate solution, we use simple geometric observations to roughly place these points. In this paper, we demonstrate how to place four and five points on the T set. From observation, it is always suitable to put one point on the intersection of the circle defined by Eq. (3) and the circle defined by Eq. (5). Thus,

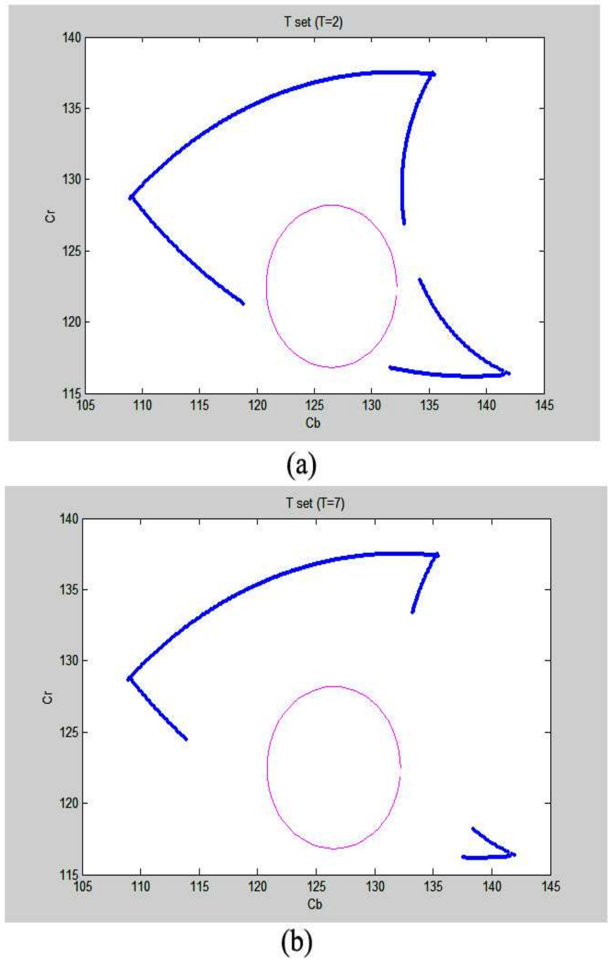
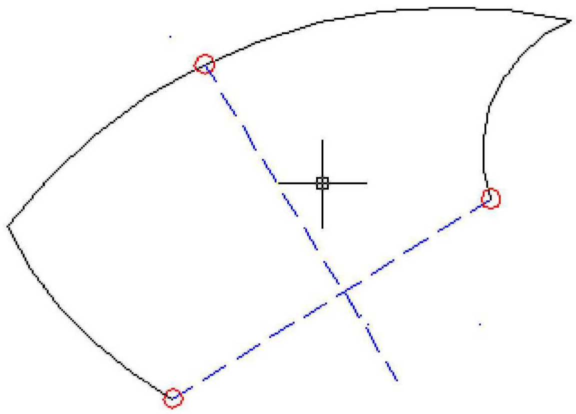
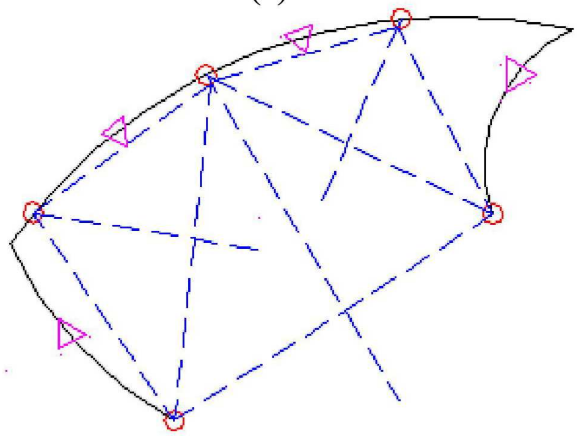


Fig. 8. Illustration of T set

the number of points needed for the other portion of the T set reduces to three and four. We use very simple and fast geometric relationships to roughly equally place points, since the process of increasing T and decreasing S will not be fast unless a simple placement algorithm is used. Figure 9 illustrates how this simple strategy generally works on an odd and even number of points. In the case of four points, we always choose the two endpoints of the T set as the placement of the second and third position. The last position is chosen as the intersection of the bisector and the partial circle. Three of the selected points are shown using small red circles in Figure 9(a). From the properties of a bisector, we know that the second, third and fourth points are equally placed. If $T = S$ then the minimum distance from the selected four points to the existing color circle is equal to the minimum distance among the selected four points. In the case of five points, we use the same bisector rule to determine the rest of the four points which are roughly equally placed on the T set. The selected points are shown using small red triangles in Figure 9(b). It is not difficult to deduce that for this case the minimum distance from the selected points to the existing color circle is slightly larger than the minimum



(a)



(b)

Fig. 9. Principles of point placement

distance among the selected points.

The chosen points corresponding to the desired practical Cb and Cr colors are mapped back to theoretical color values using the principles discussed in the previous section. The theoretical colors using the proper choice of luminance which is based on Eq. (2) are transformed back to RGB space for consistency with common printing programs. The following two figures show the best separable four and five colors with the environment setting shown in Figure 1. Figure 10 shows the best four separable colors. Figure 10 11 shows four of the best five separable colors, the omitted one is the same as Figure 10 (a).

Figure 12 shows the RoboCup patterns using the colors shown in Figure 910(a) and (b). The RoboCup competition uses an orange golf ball as the official ball. Experimental results are shown in Figure 10(c) and 11(d) verify the soundness of using an orange color. The official team mark colors are blue and yellow. The yellow color is a good choice with orange color while the blue color is not in this example. It can be experimentally verified that if the illumination is much brighter, then the blue color is close

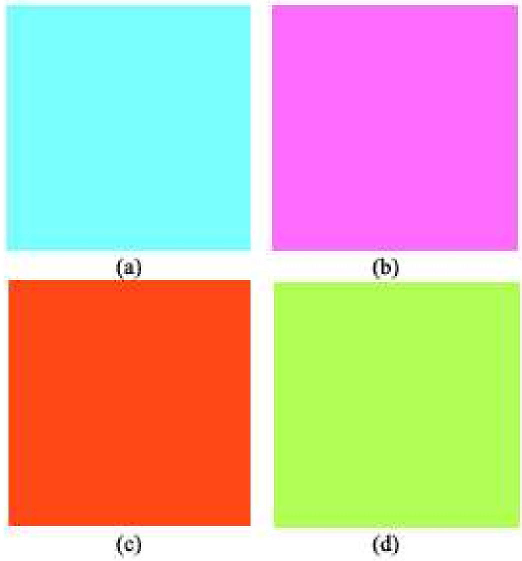


Fig. 10. Best four colors

to one of the colors learned from our algorithm, which is consistent with the official color choice. The cyan (Figure 10(a)) and pink (Figure 10(b) and Figure 11 (b)) colors are suggested by Carnegie Mellon University to be used as the official orientation mark colors after they tested many possible standard color papers. Teams also use colors similar to light green (Figure 10(d)) as orientation marks. All of these colors are shown to be good choices by our experimental results.

7. CONCLUSIONS

In this paper, we presented a practical strategy for designing a set of widely separable colors in a given environment with given equipment. Instead of modeling the complicated physical color model at a device level, it is treated as a system identification problem. Parametric curve approximation and heuristic geometric mapping are adopted as the main tool for the color design, and they proved to be efficient and effective solutions. The application of robust color choice in the RoboCup small size competition is used as an example to illustrate our strategy. The experimental results are consistent with the color choice experience of different teams participating in the RoboCup 2002 competition. The proposed general strategy can be adopted for other color choice problems which are crucial for the success of many vision applications.

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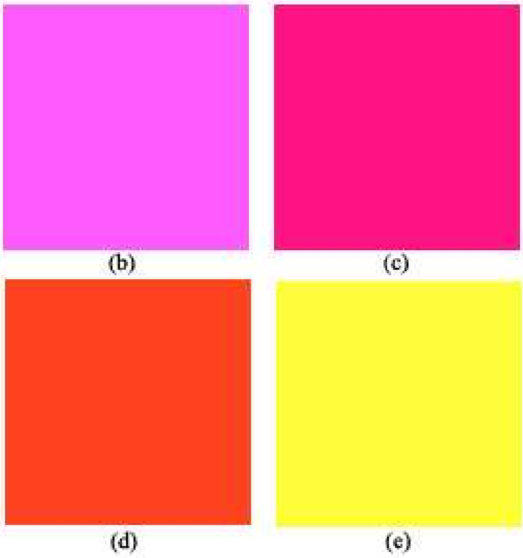

Fig. 11. Best five colors (only four are shown, the first is the same as Figure 10(a)

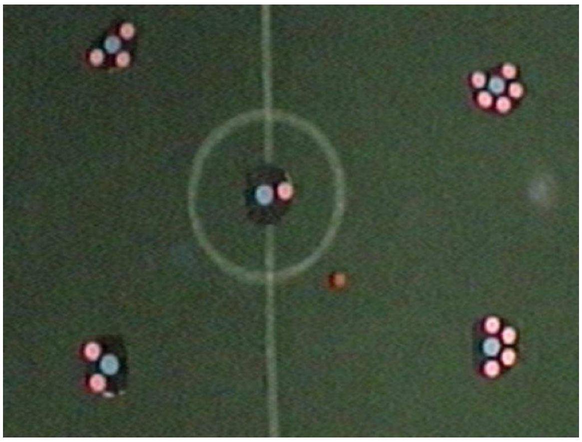

Fig. 12. Resulting RoboCup patterns

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